







## Article

# Predicting Growing Stock Volume of *Eucalyptus* Plantations Using 3-D Point Clouds Derived from UAV Imagery and ALS Data

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**Abstract:** Estimating forest inventory variables is important in monitoring forest resources and mitigating climate change. In this respect, forest managers require flexible, non-destructive methods for estimating volume and biomass. High-resolution and low-cost remote sensing data are increasingly available to measure three-dimensional (3D) canopy structure and to model forest structural attributes. The main objective of this study was to evaluate and compare the individual tree volume estimates derived from high-density point clouds obtained from airborne laser scanning (ALS) and digital aerial photogrammetry (DAP) in *Eucalyptus* spp. plantations. Object-based image analysis (OBIA) techniques were applied for individual tree crown (ITC) delineation. The ITC algorithm applied correctly detected and delineated 199 trees from ALS-derived data, while 192 trees were correctly identified using DAP-based point clouds acquired from Unmanned Aerial Vehicles (UAV), representing accuracy levels of respectively 62% and 60%. Addressing volume modelling, non-linear regression fit based on individual tree height and individual crown area derived from the ITC provided the following results: Model Efficiency (Mef) = 0.43 and 0.46, Root Mean Square Error (RMSE) = 0.030 m<sup>3</sup> and 0.026 m<sup>3</sup>, rRMSE = 20.31% and 19.97%, and an approximately unbiased results (0.025 m<sup>3</sup> and 0.0004 m<sup>3</sup>) using DAP and ALS-based estimations, respectively. No significant difference was found between the observed value (field data) and volume estimation from ALS and DAP (*p*-value from *t*-test statistic = 0.99 and 0.98, respectively). The proposed approaches could also be used to estimate basal area or biomass stocks in *Eucalyptus* spp. plantations.

**Keywords:** unmanned aerial vehicles (UAV); forest inventory; volume; canopy height model (CHM); object based image analysis (OBIA); structure from motion (SfM)

## 1. Introduction

Sustainable forest management demands accurate information that can be obtained efficiently and rapidly [1] in order to describe forest structure and quantify forest resources [2]. However, although accurate, traditional forest inventory is resource- and time-consuming, indicating the need for either alternative or complementary methods that may overcome the drawbacks of field data acquisition [3]. In addition, although field-measured data are commonly assumed to be ground truth values for remote sensing estimations, the associated errors tend to be large [3–6].

A number of alternatives to traditional field-based measurement of morphological parameters for characterizing three-dimensional (3D) structure of trees and canopies have emerged [4,7]. Airborne Laser Scanning (ALS), Digital Aerial Photogrammetry (DAP) and Terrestrial Laser Scanning (TLS) have become widely established as forest mapping and monitoring methods [8–11]. In the last two decades, DAP, ALS (e.g., [12–14]) or a combination of these methods (e.g., [15–17]) have been increasingly used to support forest inventories at different scales.

ALS has been the primary source of 3D data on forest vertical structure since the 1990s [18,19]. There has been an abundance of research demonstrating the utility of ALS for predicting forest biophysical variables to support forest inventories at individual tree- and stand-level [20,21]. Since the late 2000s DAP has provided a promising alternative, as the accuracy of stand-based estimates has been found to be similar to that achieved through ALS, at much lower cost [17,22,23].

Baltsavias [12] provided a comprehensive comparison of DAP and ALS data, highlighting the advantages and disadvantages of both technologies with regards to acquisition, accuracy, maturity and costs. Although ALS data have many advantages (e.g., direct measurement of height, higher penetration through the vegetation), DAP still represents an essential source of data for the forest inventory analyses. In fact, photogrammetric software has developed rapidly in the past 15–20 years. Since the first studies [24], advances in computer vision, image matching algorithms and computing power have promoted the use of aerial images for generating high-resolution 3D data by image matching [25]. Many photogrammetric software packages (proprietary and open-source) have been developed, offering unparalleled opportunities to produce 3D data from 2D image collections with high overlap.

Recent advances in sensors and in image processing –particularly Structure from Motion (SfM) technology– have also enabled the extraction of dense point clouds obtained by DAP [16,24,26–29]. In this sense, DAP derived from SfM is an emerging source of 3D data, reaching quality standards close to those provided by ALS [25,30]. works by [26,31–33] pointed out the potential of DAP for forest applications. During the past five years in particular, there has been an increasing interest in the use of DAP to generate 3D data analogous to ALS data, in order to support forest inventories [17,22,25,34–39]. This interest can be attributed to the need to optimize costs while improving the temporal resolution.

Unmanned Aerial Vehicles (UAVs), also known as drones or Unmanned Aerial Systems (UAS), have emerged as a cost-effective alternative to conventional methods based on manned fixed-wing aircraft or helicopters for DAP imagery and ALS data collection [40–43]. Since the first studies in which UAV-derived data was used for forest inventory purposes [44,45], UAV-based forestry applications of both ALS and DAP have increased substantially [40,46–52]. Indeed, ALS and Red-Green-Blue (RGB) sensors mounted on UAV platforms are becoming cost-effective tools for monitoring forest structure because of their high spatial and temporal resolution, achieved by the low flight height, operational flexibility and relatively low cost of the flight surveys, which meet most of forest managers requirements [53]. In particular, light UAVs equipped with inexpensive consumer grade cameras have recently appeared as a feasible option for monitoring 3D forest structure [54]. In addition, multi-temporal UAV-acquired data can also be used for rapid, accurate and cost-effective tree growth assessment, providing up-to-date information to support decision-making in forest management [48,54–58].

Two main strategies have been adopted for DAP and ALS-based analysis in forestry inventories: (i) the Area-Based Approach (ABA), a distribution-based technique which typically provides data at stand level, and (ii) the individual tree crown (ITC) delineation, in which individual tree crowns,

heights and positions are the basic units of assessment. ABA has been used with ALS and DAP to estimate forest attributes over a wide range of forest types including Temperate (e.g., [59]), Boreal (e.g., [13,14,17,34,60]), Atlantic (e.g., [61,62]), Tropical (e.g., [37]), Alpine (e.g., [63,64]), Mediterranean forests (e.g., [65–69]) and plantations [70]. At the stand level, results from recent research on small- to medium-sized boreal and tropical forests have demonstrated the potential use of UAV-based DAP data for estimating forest biomass [53,71]. On the other hand, ITC has also been applied to DAP point clouds [72] and to ALS clouds [73,74]. ITC presents several advantages over ABA for estimation of above-ground biomass because it can be used to derive biomass when an allometric model is available at individual tree level [75]. At the same time, it is particularly well suited for precision forestry, which usually requires information about individual trees.

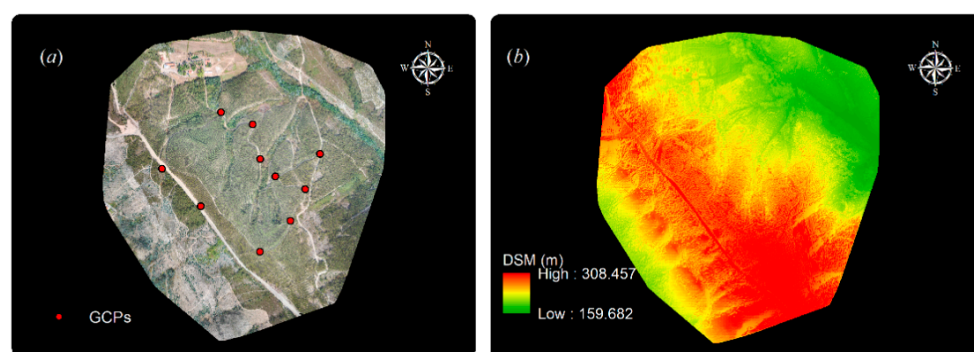
Finally, ALS and SfM approaches to tree height estimation tend to underestimate tree height [73,74,76,77]. Recent studies [77] have presented a model that explains the observed bias using probability theory, developing methods for correcting several ALS metrics used for ABA prediction of stand structure. However, few studies have evaluated the influence of this bias at individual-tree level. In this respect, further research is needed in order to analyze the influence of this bias in the individual-tree biomass and volume models for both technologies.

The objectives of this study were as follows: (i) to investigate the combined use of ALS- and SfM-derived individual-tree measurements (height and crown area) with non-linear regression models to estimate individual tree diameter and volume; and (ii) to compare the estimation of ALS- and SfM-derived individual-tree volume models to estimate growing stock volume in relation to field data.

## 2. Materials and Methods

### 2.1. Study Area

The study area is located in the municipality of Valongo (41.213° N, −8.496° W) in the district of Porto, Portugal (Figure 1). The site consists of a seven year old plantation of *Eucalyptus spp.* clonal material (G74), covering an area of 26 ha. Tree spacing was  $3.70 \times 2.5$  m, yielding a density of one tree per  $9.25 \text{ m}^{-2}$ . The elevation ranges from 163 to 294 m above the WGS84 reference ellipsoid. The terrain is topographically complex, with steep slopes (mean slope = 24.2%), and of elevation up to 131 m. The mean annual rainfall is 1568 mm, and 42.1% of the precipitation occurs between November and January. The mean annual temperature is 14.2 °C, ranging from 8.6 °C in the coldest months (December to February) to 20.1 °C in the warmest months (July to September). The study site is characterized by evenly planted trees of superior genetic material with a low mortality rate.



**Figure 1.** (a) UAV-derived RGB-orthomosaic image of the study area and 10 ground control points (GCPs) (red dots) (b) UAV-derived Digital Surface Model (DSM) generated using Pix4d® software.

### 2.2. Field Measurements and Field Volume Estimation

The field data were collected in December 2016 (to correspond to the date of acquisition of ALS data) from 6 square plots, each of approximately  $400 \text{ m}^2$  (Table 1). A total of 323 reference trees were

measured and located in 6 square plots (400 m<sup>2</sup>). The height of each tree ( $h$ , m) within the plots was measured with a Haglof Vertex IV hypsometer equipped with a T3 transponder. The diameter at breast height (1.30 m above the ground –  $d$ , cm) was measured with a steel diameter measuring tape. Field plots were remeasured using the same methods in September 2017 (matching with UAV-based DAP acquisition).

**Table 1.** Statistical description of the field data within six field plots for a total of 323 reference trees

Plot	$d$		$h$		$\hat{v}$	
	Mean		Mean		Mean	
	Dec 2016	Sep 2017	Dec 2016	Sep 2017	Dec 2016	Sep 2017
<b>P1</b>	13.2	13.4	19.4	20.9	0.13	0.14
<b>P2</b>	12.9	13.3	18.8	19.9	0.12	0.15
<b>P3</b>	13.4	13.8	18.6	20.0	0.13	0.15
<b>P4</b>	13.8	14.1	18.8	19.8	0.13	0.15
<b>P5</b>	13.7	14.0	18.3	19.7	0.13	0.15
<b>P6</b>	13.8	14.2	17.6	19.1	0.13	0.14
Min.	5.3	5.4	9.9	10.3	0.01	0.01
Mean	13.5	13.8	18.6	19.9	0.13	0.14
Max.	17.3	17.8	22.8	23.5	0.24	0.26
SD	1.7	1.7	1.5	1.6	0.03	0.04

Average (Mean), minimum (Min), maximum (Max) and standard deviation (SD), values of the individual tree diameter ( $d$ , cm), height ( $h$ , m) and field data volume estimation ( $\hat{v}$ , m<sup>3</sup>).

In order to obtain accurate positions of the trees, topographic surveys were conducted to determine the position of the center of each tree within the plots. A Trimble® TSC3 GPS controller with Trimble® R8s Integrate GNSS System Antenna (Trimble, Sunnyvale, CA, USA) (dual-frequency real-time kinematic receiver –RTK) was used to determine the coordinates of a densified geodetic network for the study area by applying real time kinematic (RTK). Based on the network established with GPS, a topographic survey of the plots was conducted using a Trimble® M3 Robotic Total Station (Trimble, Sunnyvale, CA, USA). Observations on the position of each tree within the plot were made during the survey.

Field-derived volumes were estimated using the Equation (1), provided by [78].

$$\hat{v} = 0.2105 \left( \frac{d}{100} \right)^{1.8191} h^{1.0703} \quad (1)$$

where  $\hat{v}$  is the estimated volume (m<sup>3</sup>),  $d$  is the diameter (cm) at the breast height (1.30 m) and  $h$  is the tree height (m).

### 2.3. ALS Acquisition

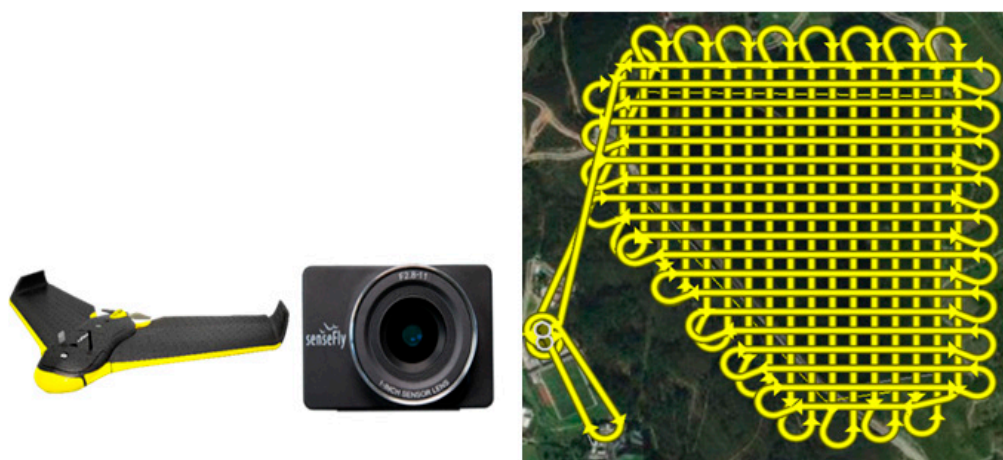
The airborne surveys were conducted on 17 December 2016, covering an area of 100 ha. The data were captured with Leica ALS80-HP laser scanner operating at pulse rate of 704 kHz, field of view of 6.5° and scan rate of 73.5 Hz, which was mounted on a Cessna airplane that flew the area at an approximately flight altitude of 2750 m.a.s.l and an average speed of 250 km.h<sup>-1</sup>. The overlap between sweeps was 30%, achieving an average laser pulse density of 43.33 pulses m<sup>-2</sup>.

### 2.4. UAV Data Acquisition and Use

The airborne surveys were conducted on 6 September 2017. An RGB S.O.D.A. 10.2 (20 MP) camera (senseFly Co, Cheseaux-Lausanne, Switzerland) was mounted, with nadir view, on a fixed-wing UAV (SenseFly eBee) (Figure 2). The camera, which was equipped with a 12.75 × 8.5 mm sensor



and  $5472 \times 3648$  pixels detector, was used in manual mode. Exposure settings (ISO 150 and shutter speed of  $1/1000$  s) were set before each take-off according to the light conditions. This provided  $\sim 6$  cm  $\text{pixel}^{-1}$  resolution for a variable altitude above ground level, which is especially useful in areas of diverse elevation range such as mountainous regions. Atmospheric conditions during the airborne surveys were characterized by calm winds, clear lighting at the flight time (between 11.30 am and 12.15 pm) to minimize the effect of shadowing. Flight parameters were determined using eMotion V. 3.2.4 flight planning and monitoring software. The flight plan covered the entire study area with longitudinal and lateral overlaps of 85% in both cases. The flight line spacing was 25 m (Figure 2). In total, 744 images were used to generate orthomosaics and Digital Surface Models (DSMs) by the SfM image reconstruction process. Two-block flights were required to capture the entire forest study area (the orthomosaic covered an area 103.70 ha with average Ground Sample Distance (GSD) of 5.95 cm).



**Figure 2.** UAV Camera (left) and flight design (right).

### 2.5. 3D Model Generation and Preprocessing Point Clouds

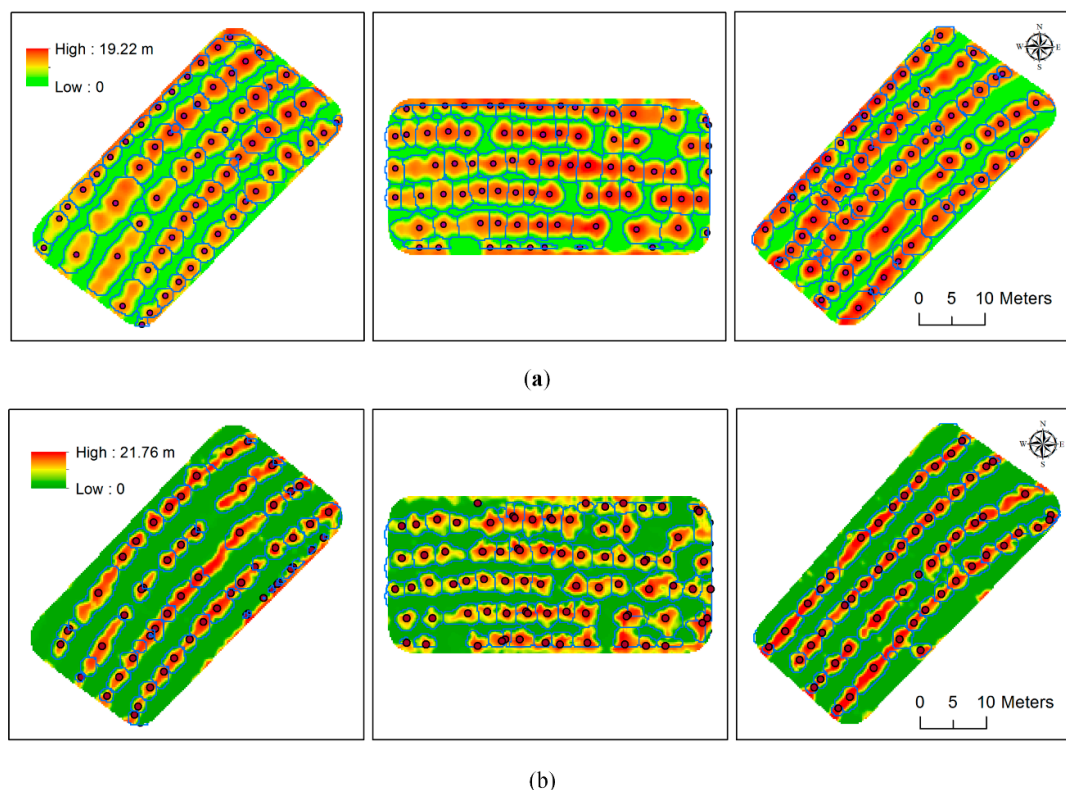
The absolute orientation of the aerial photos was determined using aerotriangulation techniques implemented in pix4D 3.3.29 (pix4D®, Ecublens, Switzerland). A set of 10 ground control points (GCPs) measured in the field with topographic methods was used to georeference the SfM mosaics to a projected coordinate system for both datasets. The ground control photogrammetric points (GCPs) were captured with a Trimble TSC3 controller and a Trimble R8s GNSS antenna (RTK precision 8 mm + 1 ppm Horizontal/15 mm + 0.5 ppm Vertical) mounted on a pole. The GCPs markers comprised a set of  $1 \times 1$  m cross-shaped white painted timber planks with some black and white  $50 \times 50$  cm painted checkerboards. For reliable accuracy of GPS measurement, all GCPs were located in open areas with no canopy cover. At each point, GPS signals were logged in RTK–global navigation satellite system (GNSS) mode. The recordings were processed with real-time correction data retrieved from the fixed base station in Gaia (Porto) (latitude:  $41^{\circ}06'21.67048''$  N, longitude:  $8^{\circ}35'20.73434''$  W, and ellipsoidal elevation: 287.63 m above the WGS84 reference ellipsoid).

Photogrammetric point clouds were computed using SfM techniques, implemented in Pix4D 3.3.29. The matching parameters for point cloud densification were set as follows: multiscale, image scale =  $1/2$  (half image size) and point density = 'optimal'. The minimum number of matched images was also set to 3.  $\text{DEM}_{\text{SfM}}$  was generated from the ground points by using a natural neighbor interpolation technique implemented in Pix4D (additional details of the algorithms are proprietary and were not disclosed by Pix4D).

The ALS and SfM point clouds preprocessed using FUSION/LDV 3.60 software [79] and LasTools [80]. For more details of point cloud processing see details in [74]. Finally, two CHMs ( $\text{CHM}_{\text{SfM}}$  and  $\text{CHM}_{\text{ALS}}$ ) were obtained by subtracting the DEMs ( $\text{DEM}_{\text{ALS}}$  and  $\text{DEM}_{\text{SfM}}$ ) from the DSMs ( $\text{DSM}_{\text{ALS}}$  and  $\text{DSM}_{\text{SfM}}$ ) in the FUSION LiDAR Toolkit [79].

## 2.6. ITC Process to Derive ALS- and SfM-Variables

Individual tree position (X and Y coordinates), height ( $h_{SfM}$ ,  $h_{ALS}$ ) and crown area ( $ca_{SfM}$ ,  $ca_{ALS}$ ) were retrieved from the respective CHM<sub>SfM</sub> and CHM<sub>ALS</sub> (Figure 2). Resampling of the CHMs to 20 cm resolution and subsequent smoothing with mean filter ( $5 \times 5$  window) in the case of ALS and median filters ( $3 \times 3$  window) for SfM were conducted using the FUSION LiDAR Toolkit [79]. Crown delineation followed the procedure detailed in [81]. The process is divided into three main phases: segmentation, classification and iterative watershed segmentation. The *Chessboard Segmentation* algorithm was used to split the image into square image objects. In the second phase, a *Classification* algorithm was used to classify image objects from the smoothed CHM. Objects with an elevation value of less than 5 m were classified as gaps. The threshold was established empirically from field observations and by trial-and-error tests. The remaining objects were assigned to the ‘temporary canopy’ class. These objects were used to locate tree tops and delineate tree crowns in the following iterative watershed segmentation processes. In the iteration, the *Find Local Extrema* algorithm was used to classify the image objects of the ‘temporary canopy’ class, which fulfills a local extreme condition according to image object features within a search domain in their neighborhoods. However, because of the forest stand and tree species characteristics, the initial maximum search domain used in the iterative process (see Figure 3 in [81]) to detect top trees was changed from 5 to 3, and 4 interactions were applied. A search with a variable square window enables detection of apices of trees with a large variety of crown sizes. Objects less than 3 m away from any detected tree top were retained in the ‘temporary canopy’ class (candidates for watershed) and any other objects were disregarded. This distance was the maximum observed crown width in the plots, which was considered the limit for crown growing in the next step. Then, the crown delineation results (Figure 3) and tree top positions were exported in ESRI<sup>TM</sup> shapefiles as vector polygons and points respectively, for subsequent analysis.



**Figure 3.** Examples of the canopy height models (cool to warm colors representing low to high heights), crown delineation (blue lines), and tree top positions (red dots) within example plots using airborne laser scanning (ALS) (a) and Structure from Motion (SfM) (b).

## 2.7. Individual Tree Volume Estimation

Volume equation (Equation (1)) requires the measurement of tree diameter or circumference, which is not available from UAV imagery. We therefore tested two approaches for estimating ALS- and SfM-derived individual-tree volumes ( $v_{SfM}$  and  $v_{ALS}$ ) (Figure 4). In the first approach, the multiplicative (power function) model in Equation (2) was fitted using  $d$  (from field data) as the dependent variable and the pairs of explanatory variables  $h_{SfM}$ ,  $ca_{SfM}$  for SfM, or  $h_{ALS}$ ,  $ca_{ALS}$  for ALS. The predicted diameter obtained by each method ( $d_{SfM}$  and  $d_{ALS}$ ) and their respective height estimates ( $h_{SfM}$  and  $h_{ALS}$ ) were then included as independent variables in Equation (1) to predict the individual volumes for the subset of 192 trees for ALS and 199 for SfM ( $v_{SfM}$  and  $v_{ALS}$ , respectively). In the second approach, the multiplicative (power function) model in Equation (3) was also fitted to predict  $v_{SfM}$  and  $v_{ALS}$  for the 192 and 199 trees respectively, but  $v$  was considered a dependent variable (estimated using the field-measured  $d$  and  $h$  in Equation (1)), and the pairs  $h_{SfM}$ ,  $ca_{SfM}$  (from SfM) or  $h_{ALS}$ ,  $ca_{ALS}$  (from ALS) were considered explanatory variables, without the need to estimate the diameters.

$$\hat{d} = h^{\beta_0} ca^{\beta_1} + \varepsilon \quad (2)$$

$$\hat{v} = h^{\beta_0} ca^{\beta_1} + \varepsilon \quad (3)$$

where  $\hat{v}$  is the estimated volume ( $m^3$ ),  $\hat{d}$  is the estimated tree diameter (cm),  $h$  is the tree height (m),  $ca$  is the canopy area ( $m^2$ ), generated from ALS or SfM,  $\beta_0$ ,  $\beta_1$ , are the exponential parameters to be estimated by non-linear regression analysis; and  $\varepsilon$  is the additive random error. The models were fitted using the Non-linear Least Squares *nls* function implemented in the *BASE* package of R software (R Core Team, 2018).

Finally, the Model Efficiency (Mef, Equation (4)), the overall root mean square error (RMSE, Equation (5)), the relative root mean square error (rRMSE, Equation (6)) and the Bias (Equation (7)) were computed in order to determine the accuracy of ALS and SfM models for estimating diameter and volume with the second approach. Mef compares predictions directly with observed data using a statistic analogous to  $R^2$  [82]. This statistic provides a simple index of performance on a relative scale, where 1 indicates a ‘perfect’ fit, 0 reveals that the model is no better than a simple average, and negative values indicate a poor model.

$$Mef = 1 - \left( \frac{(n-1) \sum_{i=1}^n (y_i - \hat{y}_i)^2}{(n-p) \sum_{i=1}^n (y_i - \bar{y})^2} \right) \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (5)$$

$$rRMSE = \frac{RMSE}{\bar{y}} * 100 \quad (6)$$

$$Bias = \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{n} \quad (7)$$

where  $n$  is the number of trees;  $y_i$  is the field-measured tree diameter  $i$ ;  $\bar{y}$  is the the mean observed value for the field-measured diameters;  $\hat{y}_i$  is the estimated value of diameter derived from the non-linear regression model and  $p$  is the number of parameters in the models.

Finally, using the correctly detected and delineated trees,  $d$  was compared with  $d_{SfM}$ ,  $d_{ALS}$  and  $v$  with  $v_{SfM}$ ,  $v_{ALS}$  in the subsample of 192 trees for SfM and 199 for ALS, respectively. Estimated and observed values were plotted and visually examined. A paired  $t$ -test was conducted to compare ALS- and SfM-predicted variables ( $d_{SfM}$ ,  $d_{ALS}$ ,  $v_{SfM}$ , and  $v_{ALS}$ ) to verify the significance of the deviations between the observed and estimated values. However, these deviations were previously checked using

the Shapiro-Wilk test [83], which indicated that the distributions meet the assumption of normality. The tests were conducted at a 5% significance level.

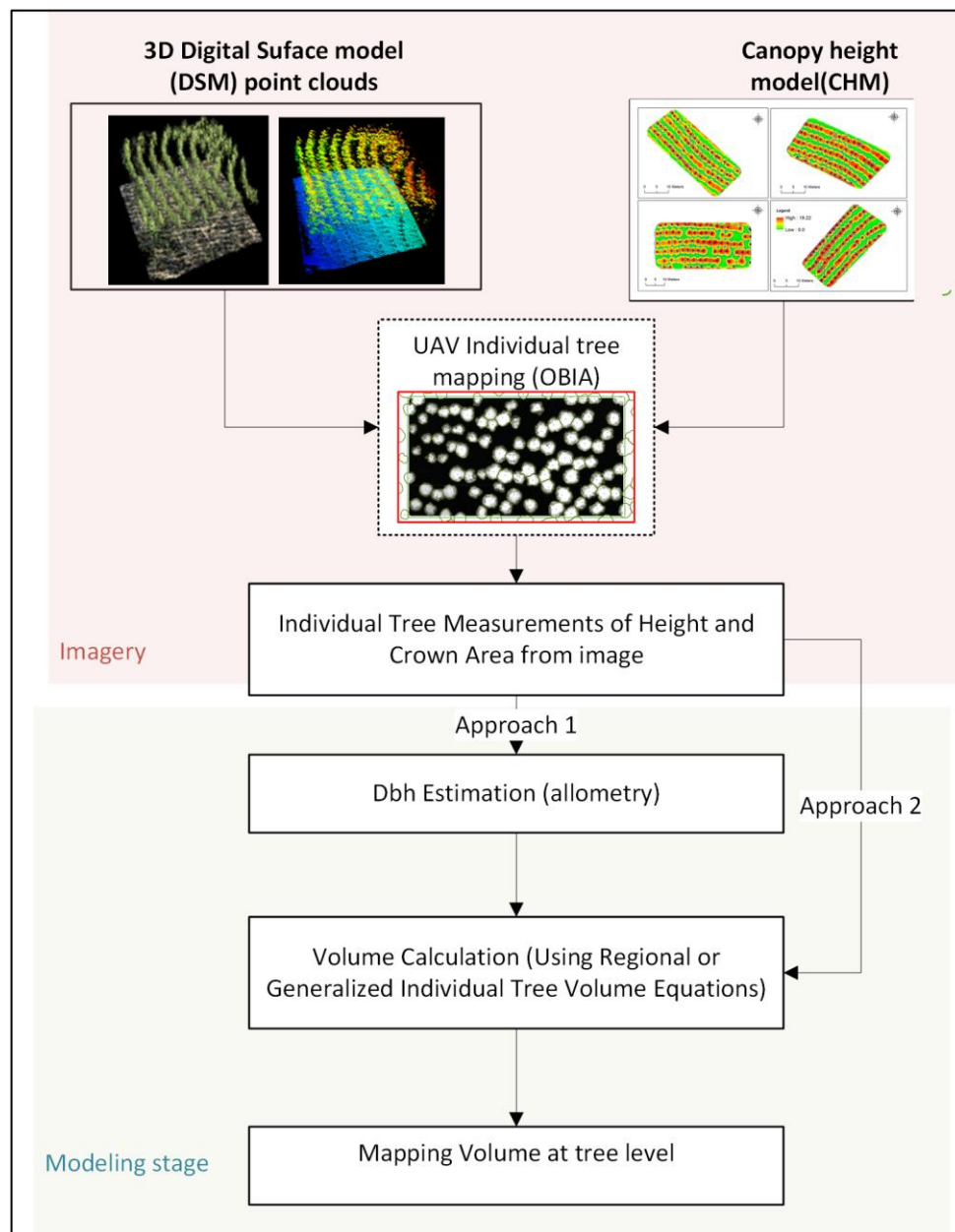


Figure 4. Summary steps of individual tree crown (ITC) to map volume.

### 3. Results

#### Field, ALS and SfM Volume Estimation

Table 2 shows the parameter estimates and goodness-of-fit statistics for the models used to predict  $d$  (cm) in the first approach, and  $v$  directly estimated by SfM- and ALS-variables in the second approach.

In the first approach, non-linear regression yielded an  $Mef$  value of 0.45 for the SfM-estimated diameter and 0.47 for ALS-estimated diameter (RMSE = 1.17 and 1.12 cm, rRMSE of 8.49 % and 8.31%, respectively). Although the UAV-based DAP method tends to underestimate tree height relative to field measurements (hypsonometers), there was no appreciable bias throughout the observed diameter (Figure 5a,b). The bias values (0.38 and 0.35 cm) indicated a slight tendency to overestimate the initial diameter values from field data (Figure 5a,b). On the other hand, although  $d$  was not directly measured

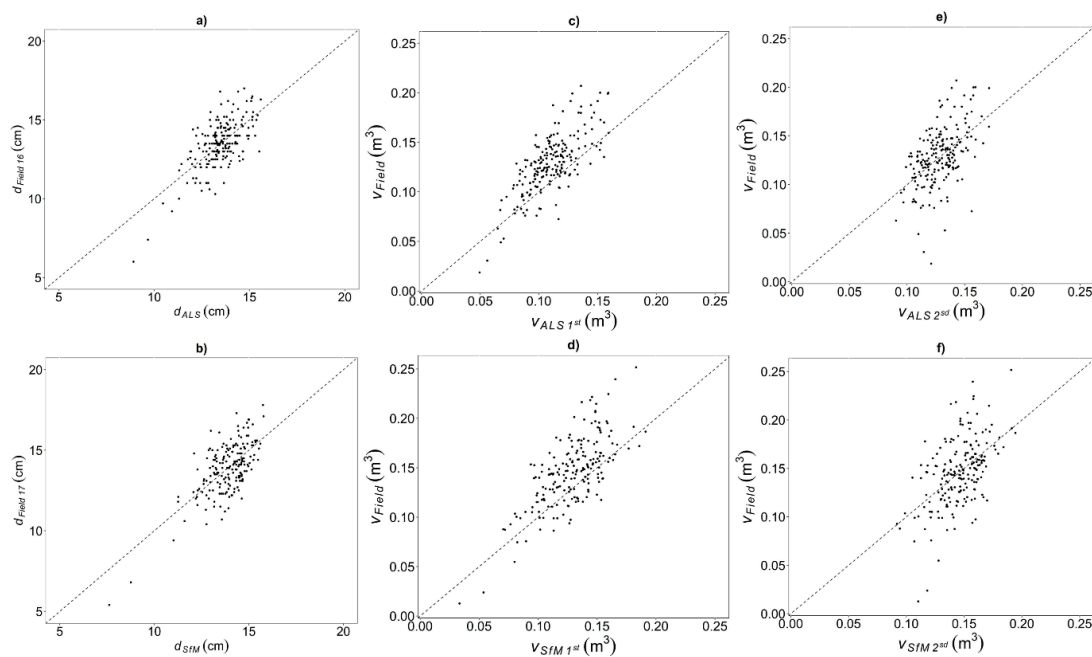


in CHMs derived from UAV and ALS,  $h_{SfM}$  and  $h_{ALS}$  were, and these variables were significant in the SfM and ALS equations. For  $d_{SfM}$  and  $d_{ALS}$  modelling, the crown area ( $ca_{SfM}$  and  $ca_{ALS}$ ) was also statistically significant ( $p < 0.05$  and  $p < 0.001$ , respectively).

**Table 2.** Models selected for estimating SfM and ALS derived individual tree diameter and volume.

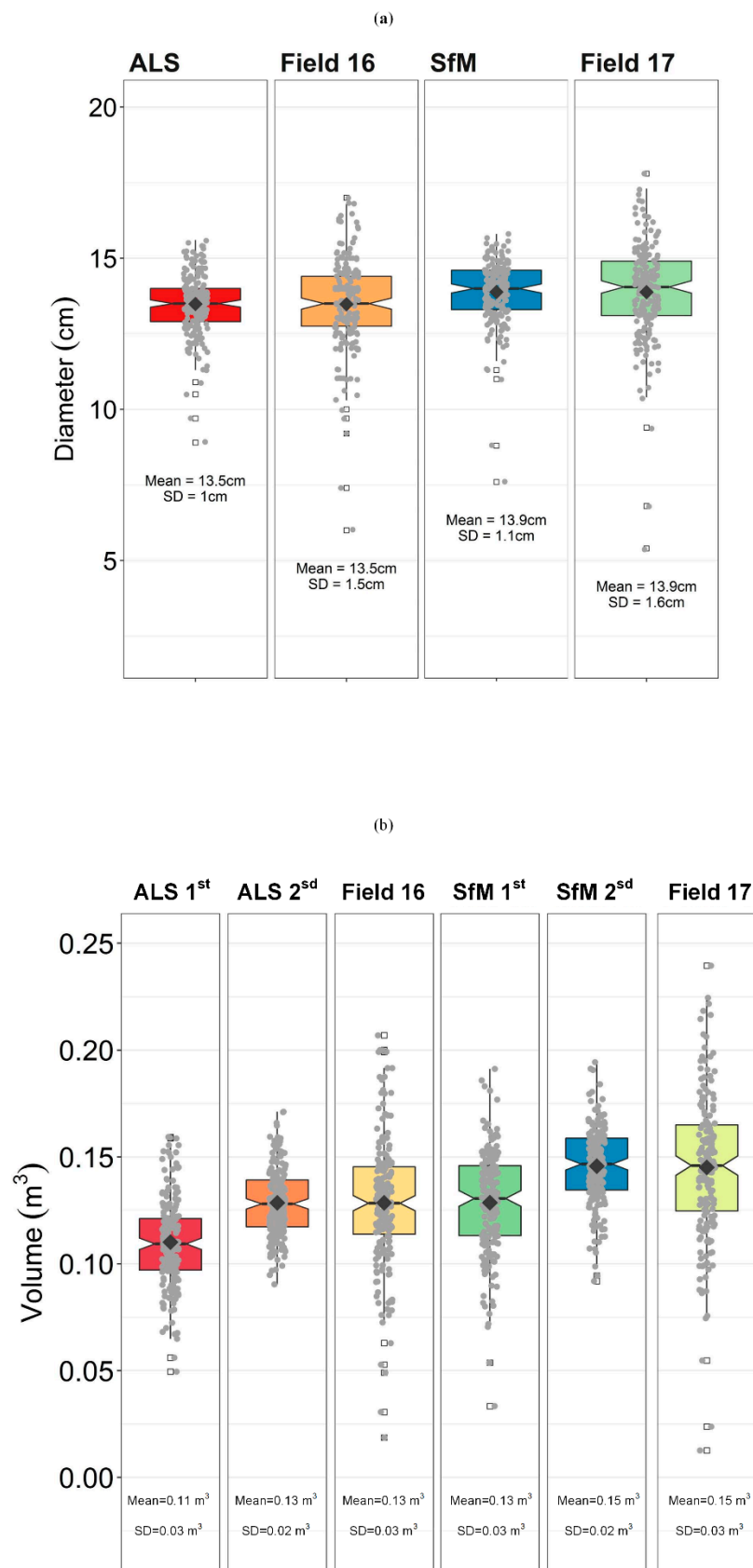
Approach	Dependent variable	Predictors	Parameter estimate	Standard error	<i>p</i> -value	Mef	RMSE (cm)	rRMSE (%)	bias (cm)
1st	$d_{SfM}$	Constant	0.863	1.170	< 0.001	0.45	1.17	8.49	0.38
		$h_{SfM}$	0.907	0.108	< 0.001				
		$ca_{SfM}$	0.037	0.037	0.013				
	$d_{ALS}$	Constant	0.564	0.151	< 0.001	0.47	1.12	8.31	0.35
		$h_{ALS}$	1.042	0.090	< 0.001				
		$ca_{ALS}$	0.062	0.015	< 0.001				
Approach	Dependent variable	Predictors	Parameter estimate	Standard error	<i>p</i> -value	Mef	RMSE (m <sup>3</sup> )	rRMSE (%)	bias (m <sup>3</sup> )
2nd	$v_{SfM}$	Constant	0.004	0.002	0.082	0.43	0.030	20.31	0.0016
		$h_{SfM}$	1.192	0.201	< 0.001				
		$ca_{SfM}$	0.151	0.035	< 0.001				
	$v_{ALS}$	Constant	0.001	0.000	0.106	0.46	0.026	19.97	0.0004
		$h_{ALS}$	1.828	0.224	< 0.001				
		$ca_{ALS}$	0.024	0.037	< 0.001				

$h_{SfM}$  and  $h_{ALS}$  are the SfM and ALS-derived tree height (m),  $ca_{SfM}$  and  $ca_{ALS}$  are the SfM and ALS-derived individual crown area (m<sup>2</sup>), Mef is the model efficiency statistic, RMSE is the root mean squared error and rRMSE is the relative root mean square error.



**Figure 5.** Scatter plots of ALS and SfM-derived variables against field-derived variables: (a) field-measured tree diameter ( $d$ ) against ALS-estimated tree diameter ( $d_{ALS}$ ); (b) field-measured tree diameter ( $d$ ) against SfM-estimated tree diameter ( $d_{SfM}$ ); (c) field-estimated volume ( $v_{field}$ ) against ALS-estimated volume ( $v_{ALS}$ ) using the first approach; (d) field-estimated volume ( $v_{field}$ ) against SfM-estimated volume ( $v_{SfM}$ ) using the first approach; (e) field-estimated volume ( $v_{field}$ ) against ALS-estimated volume ( $v_{ALS}$ ) using the second approach; (f) field-estimated volume ( $v_{field}$ ) against SfM-estimated volume ( $v_{SfM}$ ) using the second approach.

Plot	$d_{ALS}$ (cm)		$d_{SfM}$ (cm)		$v_{ALS}$ (m <sup>3</sup> )			$v_{SfM}$ (m <sup>3</sup> )		
	ALS	Field 16	SfM	Field 17	ALS 1 <sup>st</sup>	ALS 2 <sup>sd</sup>	Field 16	SfM 1 <sup>st</sup>	SfM 2 <sup>sd</sup>	Field 17
P1	14.1	13.3	14.3	13.4	0.13	0.15	0.13	0.15	0.15	0.14
P2	13.4	12.5	14.0	13.4	0.11	0.14	0.11	0.13	0.15	0.14
P3	13.1	13.3	13.9	14.0	0.10	0.13	0.12	0.12	0.14	0.15
P4	13.4	13.8	13.8	14.3	0.11	0.14	0.13	0.12	0.14	0.15
P5	13.5	13.8	14.0	14.2	0.11	0.14	0.13	0.13	0.15	0.15
P6	13.2	14.2	13.1	14.0	0.11	0.16	0.14	0.12	0.14	0.14
Min.	8.9	6.0	7.6	5.4	0.05	0.05	0.02	0.03	0.09	0.01
Mean	13.5	13.5	13.9	13.9	0.11	0.15	0.13	0.13	0.15	0.15
Max.	15.6	17.0	15.8	17.8	0.16	0.20	0.21	0.19	0.19	0.25
SD	1.0	1.5	1.1	1.6	0.02	0.02	0.03	0.02	0.02	0.03
$t$ -test $p$ -value	0.98		0.98		<0.001	0.99		<0.001	0.98	



**Figure 6.** Box plot of field-measured and remotely sensed estimated values of diameter (a) and volume using the 1st approach and 2nd approach (b). The lower and upper areas of the boxes represent the 5th and 75th percentiles and the horizontal band represents the median. The upper and lower whiskers extend from to the highest and lowest value respectively within the 1.5 times the interquartile range.

#### 4. Discussion

Both  $v_{SfM}$  and  $v_{ALS}$  were accurately estimated from UAV photograph and ALS-based 3-D point clouds using SfM- and ALS-variables extracted automatically from their respective CHMs. Although ALS-based methods and UAV-based DAP methods tend to underestimate tree height [73,74,77], relative to field measurements (hypsonometers), no appreciable biases in the observed diameter and volume range estimations occurred with either technologies in the 2nd approach.

Variables derived from the automated processing of ALS and UAV-based DAP with ITC delineation ( $h_{SfM}$ ,  $h_{ALS}$ ,  $ca_{SfM}$ , and  $ca_{ALS}$ ) were found to be significant explanatory variables for predicting  $d$  and  $v$  in both approaches; however, the Mef and RMSE values for diameter models indicate poorer fits than reported in some recent studies in *P. pinea* plantations [57] (Mef = 0.79, rRMSE = 4.99%,  $n$  = 50 trees) and Japanese Cypress (*Chamaecyparis obtusa*) [84] ( $R^2$  = 0.79,  $n$  = 51 individual trees where  $d$  ranged from 11 to 58 cm) using UAV-based DAP point clouds.

In the case of ALS-based diameter models, our results were similar in terms of  $R^2$  to those reported by Chisholm et al. [85], who extracted forest below-canopy information using UAV-based LiDAR and developed post-processing software to detect trees and to estimate their diameters ( $R^2$  = 0.45, rRMSE = 25.1%). Finally, the results were also similar in terms of rRMSE to those reported by Cosenza et al. [86] in a eucalyptus plantation in Brazil (rRMSE = 9%), for an exponential equation with  $h$  as explanatory variable. Cosenza et al. [86] also observed a slight tendency to overestimate the initial diameter values (bias = 0.12 cm).

Studies conducted in *Picea abies* (L.) H. Karst. and *Pinus sylvestris* L. stands in Sweden and in *Pinus taeda* L. stands in the SE United States found that ALS-derived  $h$  and crown diameter ( $cd$ ) explained up to 87% and 91% of the variance associated with the estimation of  $d$ , with RMSE of 3.8 and 4.9 cm, respectively [87,88]. Zhao et al. [89] reported an  $R^2$  value of 0.87 and a RMSE value of 5.2 cm for ALS-derived tree dimension variables including  $h$ ,  $cd$  and crown base height in *P. taeda* stands. In this study, the diameter equation based on ALS-derived variables performed well, although the values of Mef were slightly lower than some of those reported for other species [87,88].

Regarding volume modelling, the performance of the  $v_{ALS}$  and  $v_{SfM}$  estimates for predicting tree volume directly from ALS- and SfM-derived variables (the second approach,  $R^2$  = 0.46,  $R^2$  = 0.43; RMSE = 0.026 m<sup>3</sup>, RMSE = 0.030 m<sup>3</sup>; respectively) was lower than that obtained in different conifer species ( $R^2$  = 0.88) [88], as well as in *P. taeda* ( $R^2$  = 0.80) [89] and *P. pinea* (Mef = 0.84 – 0.85) [57]. The mean differences between the deviations of field volume and the ALS- or SfM-derived volume were statistically significant using the 1st approach. The tendency of ALS and UAV-based DAP technologies to underestimate  $h$  may be the main reason for the underestimation of  $v$  with 1st approach. It should be also borne in mind that the ALS and UAV-based DAP, as a tree height estimation technique, tends to underestimate tree height (e.g., DAP [39,90,91], UAV-based DAP [47,74,76,92] and ALS [73,77,93–95] point cloud data). However, our volume modelling results suggest that this bias may not influence in volume estimations using the 2nd approach, leaving open the question as to when and where specific models should be developed for correcting the bias at tree level depending on particular species or forest structure [77]. The results of this study are consistent with the approaches used by other authors [57,73], in which the use of linear regression improved the accuracy of tree height estimations from DAP-ALS data in terms of RMSE and bias, instead of using tree height extracted directly from the CHM to calculate the RMSEs and bias [74], as also occurred with modelling volume in the present study.

There are three possible reasons for the differences in performance for diameter models using SfM- and ALS-variables relative to other species: (i) First, broadleaved trees in particular are more challenging for both local maxima detection and delineation compared to conifer trees. (ii) Second, crown delineation remains difficult because the crowns of neighboring trees often overlap due to the high density of trees per unit area. (iii) Third, the low density of leaves in the crowns and the small size of the crowns of mature trees prevent a considerable number of laser pulses from hitting the crown (thus hampering crown delineation). As expected, the ALS cloud contributed to yielding

slightly better results for diameter and volume estimation, but we did not observe differences in terms of volume estimations. As with previous studies using DAP, ITC delineation is more affected than ALS crown delineation as UAV-based DAP has several limitations: (i) ALS is insensitive to shadows made by clouds [15], (ii) the images are strongly influenced by atmospheric conditions (e.g., wind swaying can cause problems building point clouds), solar illumination and view angles (sun, surface and sensor geometry), occlusions caused by shadows are particular problematic for generation of image-based point clouds in dense forest canopies [45,96–98]. In addition, seasonality (timing) influences underestimation of tree heights but can improve detection accuracy [99]. The allometric relationship between volume and ALS or SfM crown-derived variables could be also refined through improvements in UAV imagery acquisition and processing.

Finally, a more comprehensive examination of the effects of varying the conditions of UAV-based DAP acquisition and their implications for estimating forest inventory variables in different types of forest should be carried out using these techniques [100–102]. Many facets have not been explored with current state-of-the-art techniques. Several effects related to flight configuration (i.e., flight speed, wind effect, illumination effect), post-processing pipelines (i.e., comparing different SfM algorithms), field data collection (i.e., number of field plots) and environmental variables (i.e., effect of aspect or slope when using different DEM approaches or the DEM-independent approach) must be analyzed. Future research must also explore how the type of platform (fixed-wing versus multirotor), sensors or the type of forest (e.g., temperate, deciduous, evergreen needleleaf, and tropical forest) influence the ability of UAV-based DAP methods to accurately characterize biometric tree variables at the tree level.

## 5. Conclusions

The study findings showed that UAV-based DAP methods are useful and comparable to ALS for forest inventory and sustainable forest management in planted forests, by providing accurate estimations of forest structural attributes at the tree level. The results suggested that object-based image analysis (OBIA) provides more accurate predictive models for individual volumes of *Eucalyptus* trees based on ALS-derived and SfM-derived variables from the 3D point clouds than those obtained using indirect approaches to estimate diameter.

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